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Driving Factors of Generative AI Adoption in New Product Development Teams from a UTAUT Perspective

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ABSTRACT

Recent new product development (NPD) teams apply various generative AI (GenAI) tools in the development process, yet it is not fully understood about the factors affecting teams' adoption of these tools. This research identifies factors driving the use and attitudes toward GenAI in NPD tasks based on the Unified Theory of Acceptance and Use of Technology (UTAUT). We interviewed nine GenAI users in NPD teams and conducted a survey study with 309 participants. By exploratory factor analysis and hierarchical regressions, we identified a composite factor of performance expectancy and anthropomorphism as the strongest positive predictor of attitudes, and task-tool fitness as the strongest positive predictor of behavioral intention. Besides, we also identified significant predictors including several other factors in UTAUT and individual differences in AI self-efficacy. The findings can be used for developing UTAUT models and designing GenAI tools specific to NPD purposes.

KEYWORDS

New product design; generative AI; technology acceptance; UTAUT

1. Introduction

In New Product Development (NPD), increasing teams are leveraging Generative Artificial Intelligence (GenAI) tools for collaboration and innovation. GenAI is a type of AI system capable of creating new content in various forms including text, images, audio, video, codes, or even design solutions (Cao et al., 2023; Fang, 2023; Lim et al., 2023). In recent years, many GenAI tools, such as OpenAI GPT API and Microsoft Copilot, have targeted business teams or been embedded in enterprise collaborative platforms. NPD teams also increasingly adopt domain-specific GenAI tools such as Autodesk Dreamcatcher, RunwayML, and Jasper. Furthermore, the survey of over 1400 executives across 14 industries found that 89% of them ranked AI and GenAI as one of their top three tech priorities for 2024 (Apotheker et al., 2024), revealing the surging interest of individuals and business teams in GenAI.

To design effective GenAI tools for NPD teams, a growing interest is what factors could be associated with the teams' adoption of GenAI tools. To understand factors related to technology adoption, a widely used theory is the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). UTAUT posits that users' perceptions of the technology, such as performance expectancy, effort expectancy, social influence, and facilitating conditions, play central roles in determining the attitude and intention to use the technology. Recent studies have also applied UTAUT to study AI adoption (e.g., Strzelecki, 2023; Yin et al., 2023). They suggest major predictors of behavioral intention include performance expectancy, effort expectancy, social influence (e.g., Cabrera-Sánchez et al., 2021), price value, and habit, and major predictors of attitude include performance expectancy, effort expectancy, facilitating condition, and social influence (e.g., Sharma et al., 2024)

However, existing studies of AI adoption based on UTAUT rarely address the NPD context, whereas NPD teams present some unique features not fully captured. NPD involves collaboration and close teamwork, as professionals with diverse skills and knowledge collaborate across departments to conceptualize, design, and refine products (Cooper, 2010; Hussein et al., 2014). With this inherent need for collaboration in NPD, team members may tend to anthropomorphize AI, viewing it not merely as a tool but as a virtual member (Hsiung et al., 2023; Larson & DeChurch, 2020; Seeber et al., 2020; Zhang et al., 2021). Perceived anthropomorphism is one of the widely studied factors in research on human-AI interaction (Blut et al., 2021; Cheng et al., 2022; Rietz et al., 2019). Such feeling can be associated with trust and further a sense of intelligence or effectiveness of AI (Cheng et al., 2022; Glikson & Woolley, 2020; Moussawi et al., 2021). However, perceived anthropomorphism has been rarely considered in previous UTAUT studies of GenAI adoption.

In addition, NPD also encompasses a wide array of interdependent and complex tasks that span multiple expertise (Hussein et al., 2014), from market research, ideation,

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prototyping, development, and evaluation (Booz, Allen & Hamilton, 1982; Cooper & Kleinschmidt, 1986; Cooper, 1990; Page, 1993; Pahl et al., 2007). It requires both critical or analytical tasks and divergent creative ones. This characteristic necessitates GenAI functions tailored to specific task requirements, but it remains unclear how GenAI's compatibility with tasks contributes to users' attitudes and intentions to use.

Therefore, this study aimed to identify factors influencing teams' attitudes and intentions to use GenAI in new product development. We conducted a mixed-methods approach of interviews with NPD professionals and surveys based on UTAUT models tailored for NPD contexts. The results could further be used to develop theoretical frameworks and provide managerial or design strategies to create more effective and user-friendly GenAI tools for NPD teams.

2. Literature review

2.1. GenAI in new product development process

New product development (NPD) typically spans problem definition, idea generation, idea evaluation, business analysis, development, product testing, and commercialization (Booz, Allen & Hamilton, 1982; Cooper & Kleinschmidt, 1986; Cooper, 1990; Page, 1993; Pahl et al., 2007). Different stages involve distinct tasks or activities. Problem definition and business analysis require efforts in collecting information and data analysis. Idea generation focuses on divergently generating high-quality ideas. Idea evaluation and product testing involve evaluating, modifying, and selecting ideas or prototypes. The development stage includes engineering tasks like designing, writing, and programming in software projects.

In the problem definition and business analysis stage, decision-making heavily relies on information gathering and processing (Cooper & Kleinschmidt, 1986; Leenders et al., 2003; Thomke & Fujimoto, 2000), but limitations of human cognitive capacities hinder the efficient handling of complex data (Florén & Frishammar, 2012; Simon, 1955; Von Hippel & Tyre, 1995). GenAI emerges as a valuable aid by enhancing speed and accuracy in information comprehension and analysis. It processes vast amounts of multi-format data including texts, images, and videos (Bouschery et al., 2023; Rose, 2023; Weitzman, 2023), generating concise summaries to facilitate knowledge extraction (Bouschery et al., 2023; Murad & Martin, 2007), and offering high-level insights for decision-making (Chuma & Oliveira, 2023; Spreafico & Sutrisno, 2023). With capabilities such as sentiment analysis, GenAI transforms disorganized data into comprehensible and actionable insights, supporting decisions, minimizing risks, improving efficiency, and reducing analysts' workload (Chen et al., 2023; Kanbach et al., 2023; Kshetri et al., 2023).

The ideation generation stage aims to produce numerous diverse, high-quality ideas (Girotra et al., 2010; Maaravi et al., 2021; Sawyer, 2011). GenAI can increase ideation efficiency by generating inspirational materials or first drafts. Designers usually build mood boards for inspiration in the early stages to stimulate ideation. Instead of manually collecting cases on mood boards, they can use GenAI tools to quickly generate inspirational cases with fine details, such as images with lighting, textures, atmospherics, and unique styles (Fang, 2023). Some designers find AI-made images more inspiring, enjoyable, and useful than traditional inspiration sources like Pinterest (Cai et al., 2023). Furthermore, these AI-generated ideas can also be used as first drafts and iterated and refined by using GenAI (Bouschery et al., 2023; Selker, 2023). This design process has been used in practice by organizations such as IDEO (Syverson, 2020).

The idea evaluation stage involves assessing a large number of ideas and selecting the most promising ones for further development, including initial screening and subsequent more specific evaluations (Cooper, 2008). However, traditional expert evaluations can be costly, time-consuming, and prone to inconsistent results due to subjective opinions (Dean et al., 2006; Ferioli et al., 2010; Klein & Garcia, 2014). In the initial screening, GenAI can improve evaluation efficiency by rating ideas at scale from different perspectives, such as originality (Organisciak et al., 2023), desirability, feasibility, and viability (Mesbah et al., 2023). This enables quick identification and elimination of inferior ideas (Bell et al., 2023). GenAI also improves the consistency of evaluation results by providing ratings that are similar to those of experts but with much less variability (Meijer, 2023). In the more specific evaluations, GenAI can provide evaluation advice on various aspects to assist human evaluation (Eapen et al., 2023).

Finally, the development stage of NPD is complex and often spans over one-third of the total timeline (Page, 1993). GenAI can enhance its efficiency and productivity by aiding sketching or modeling, writing, and programming tasks. Firstly, GenAI supports sketching or modeling across design domains such as fashion, architecture, and automotive (Joibi & Eune, 2023), refining sketches, inspiring new designs (Zhang et al., 2023), creating visual assets (Liu & Zhou, 2022), and optimizing human proposals (Huang et al., 2022). Nevertheless, it occasionally produces images with some logical and structural errors (Fang, 2023). Secondly, GenAI significantly increases writing efficiency and quality (Noy & Zhang, 2023), translating between languages (Bahdanau et al., 2014), generating story text on demand (Coenen et al., 2021), and co-authoring narrative outlines (Chung et al., 2022). Third, GenAI models have proven instrumental in programming assistance, used for auto-completion (Chen et al., 2021; Kim et al., 2021), language translation (Lachaux et al., 2020), natural language to code conversion (Feng et al., 2020), and duplicate code detection (Guo et al., 2021). Tools such as OpenAI's Codex (Chen et al., 2021) increase programming speed via accurate suggestions and natural language-based code generation, though the quality and accuracy need further improvement.

2.2. Factors influencing the attitudes and intentions of using AI tools from the perspective of UTAUT & UTAUT2

To study users' adoption of new technologies, a widely applied theory is UTAUT (Unified Theory of Acceptance and Use of Technology), which explains and predicts individuals' attitudes and intentions to use by their perceptions of the technologies (Venkatesh et al., 2003). It comprises performance expectancy, effort expectancy, social influence, and facilitating conditions. The later extended version, UTAUT2 (Venkatesh et al., 2012), adds hedonic motivation, price value, and habit, further increasing the effectiveness of predicting the adoption of technologies.

Both models have been applied for AI adoption studies across multiple domains including general use (e.g., Gansser & Reich, 2021), education (e.g., Chatterjee & Bhattacharjee, 2020), healthcare (e.g., Osta et al., 2022), finance (e.g., Roh et al., 2023), and industry (e.g., Yin et al., 2023). Some studies also extend the UTAUT2 framework by incorporating additional factors such as personal innovativeness (e.g., Gansser & Reich, 2021), AI-related experience (e.g., An et al., 2023), perceived risk (e.g., Wu et al., 2022), and trust (e.g., Roh et al., 2023). We listed relevant studies in Table 1.

2.2.1. Factors in UTAUT2

Performance expectancy (PE) is the extent to which an individual believes that using the system will result in improved job performance (Venkatesh et al., 2003), and is regarded as one of the strongest predictors of behavioral intention (Venkatesh et al., 2012). In the research on AI, PE has also been found as an effective positive predictor of behavioral intention (Li, 2024; Romero-Rodríguez et al., 2023; Xiong et al., 2023) and attitude (Cao et al., 2021; Sharma et al., 2024).

Effort expectancy (EE) is an individual's perception of the easiness of using a specific technology (Venkatesh et al., 2003). The research on AI has found a positive correlation between higher EE and a more positive attitude toward AI tools, as well as an increased intention to use them in different contexts (Foroughi et al., 2023; Osta et al., 2022; Yin et al., 2023). However, its effects on behavioral intention were inconsistent in different studies using AI for general purposes. These studies indicated either no significant effects (Cabrera-Sánchez et al., 2021; García De Blanes Sebastián et al., 2022) or positive effects (Gansser & Reich, 2021; Xiong et al., 2023).

Social influence (SI) refers to the extent to which an individual perceives that others believe it is important for them to adopt a new information system or technology (Venkatesh et al., 2003). Technology, particularly social media, has created a social atmosphere that influences individuals' attitudes, intentions, and choices through interactions with reference groups, family, friends, and colleagues (Cabrera-Sánchez et al., 2021). Previous research has examined SI in various AI application contexts, and its relationship with behavioral intentions has often been found to be significant (Li, 2024; Strzelecki, 2023; Wu et al., 2022), particularly in industrial settings (Maican et al., 2023; Yin et al., 2023).

Facilitating conditions (FC) refer to the user's belief that sufficient resources and support are available for using technology in organizational contexts (Venkatesh et al., 2003). For general or industrial applications of AI, most studies indicate that FC has little impact on user's attitude and behavior intention (Cabrera-Sánchez et al., 2021; Li, 2024; Yin et al., 2023), but a positive effect on use behavior (Cabrera-Sánchez et al., 2021; Jain et al., 2022). In the context of using AI for advice or decision-making, FC has been found to positively impact user attitude (Roh et al., 2023; Sharma et al., 2024).

Hedonic motivation (HM) refers to the pleasure or enjoyment derived from using technology (Venkatesh et al., 2012). AI user studies have shown that HM increased behavioral intention in general usage (Cabrera-Sánchez et al., 2021; Romero-Rodríguez et al., 2023), but it is usually not significant or not taken into consideration for industries and other specific usage contexts (An et al., 2023; Cao et al., 2021; Maican et al., 2023).

Price value (PV) refers to the customer's perception of the ratio between the benefits and the cost of using the technology, and lower prices are associated with increased usage (Venkatesh et al., 2012). Researchers have found that PV significantly increased the intention to use AI for general purposes (Cabrera-Sánchez et al., 2021; Romero-Rodríguez et al., 2023). However, in the context of industries and other specific contexts, PV has been found to have no significant effects or not taken into consideration.

Habit is the degree to which individuals perform behaviors automatically as a result of prior learning and experience (Venkatesh et al., 2012). Habit has been found as a positive predictor of behavioral intention for general usage of AI (Gansser & Reich, 2021; Romero-Rodríguez et al., 2023), but not significant in specific contexts such as industries. In addition, researchers have found a possessive association between habit and use behavior (Strzelecki, 2023; Yin et al., 2023).

2.2.2. Other perception factors and individual differences

In previous AI adoption studies using the UTAUT and UTAUT2 models, we found factors that make significant contributions to attitude or intention to use AI but were not mentioned in the original UTAUT models, such as perceived risk. Perceived risk refers to the expectation of losses associated with purchase and acts as an inhibitor to purchase behavior (Peter & Ryan, 1976). In research on AI adoption, perceived risk has been studied across several dimensions, including privacy, security, psychological, functional, and social dimensions (García De Blanes Sebastián et al., 2022; Wu et al., 2022) and has been found to decrease attitude and behavioral intention (Xiong et al., 2023).

Relevant to perceived risk, trust is also a frequently studied factor. It has been found to increase behavioral intention in several AI user studies (e.g., Cabrera-Sánchez et al., 2021). This study investigates the effect of perceived risk but excludes trust. The major reason is that trust is intertwined with various other factors, including perception factors such as PE in UTAUT (Kraus et al., 2023; Shamszare & Choudhury, 2023), perceived usefulness (Wilson et al., 2021), perceived ease of use (Yang et al., 2015), human, AI, and contextual factors (Kaplan et al., 2023), as well as perceived risk (Xiong et al., 2023). Furthermore, some studies treated trust parallel to PE and other perception factors as an antecedent of attitude (Roh et al., 2023; Xiong et al.,

Table 1. Studies of AI adoption based on UTAUT and UTAUT2 and factors affecting attitudes, behavioral intention, and use behaviors.

	Settings			UTAUT&UTAUT2 factorsa					Additional factors	
	Application contexts	Types of AI tools	GenAI or not	PE	EE	SI	FC	Other factors	Risk-related factors	Other factors
1. General contexts										
(Gansser & Reich, 2021)	Daily activities	AI everyday applications (mobility, household, and health)	No	+BI[b,c]	+BI	+BI	/	HM: +BI Habit: +BI, +UB	Safety security: -BI (mobility and health)	Personal innovativeness: +BI
(Cabrera-Sánchez et al., 2021)	General contexts	AI mobile applications	No	+BI	/	+BI	+UB	HM: +BI PV: +BI Habit: +BI, +UB	/	Consumer trust: +BI Technology fear: −BI
(García De Blanes Sebastián et al., 2022)	General contexts	AI virtual assistants	No	/	/	/	/	Habit: +BI	/	Trust: +BI Personal innovativeness: +BI
(Romero-Rodríguez et al., 2023)	General contexts (adopted by university students)	ChatGPT	Yes	+BI	/	/	+UB	HM: +BI PV: +BI Habit: +BI, +UB	/	/
(Xiong et al., 2023)	General contexts	AI virtual assistants		+AT, BI	+AT, BI	+BI	+BI	/	Perceived risk: −AT, −BI	Trust: −Perceived risk, +AT
2. Industrial contexts										
(Jain et al., 2022)	Social development organizations	AI-enabled collaborative tools	No	+UB	+UB	+UB	+UB	/	/	AI aversion: −UB
(Yin et al., 2023)	Creative industry	GenAI	Yes	+BI	/	+BI	/	HM: +BI Habit: +BI	/	Anxiety of learning GenAI: −BI Anxiety of AI configuration: -BI
(Maican et al., 2023)	Business	GenAI (image-based)	Yes	+BI	+BI	+BI	/	/	/	Study domain (science): −BI
3. Other contexts										
(Chatterjee & Bhattacharjee, 2020)	Higher education	AI technologies	No	/	+AT	/	+EE, +BI	/	Perceived risk: −AT	/
(G. Cao et al., 2021)	Organizations (adopted by managers)	AI decision-making systems	No	+AT	+AT	/	+PE, +EE	/	Perceived threat: −AT	Personal wellbeing concerns: −AT, −BI Personal development concerns: −BI
(Wu et al., 2022)	College learning (adopted by students)	AI-assisted learning environment	No	+AT	+AT	+AT	/	/	Psychological risk: −AI Functional risk: −AT Social risk: −AT	/
(Osta et al., 2022)	Online health communities	AI chatbots	Yes	+BI, +UB	+BI, +UB	+BI, +UB	+BI, +UB	/	/	/
(Sharma et al., 2024)	Retailing (adopted by customers)	AI decision-making systems	No	+AT	+AT	+AT	+AT	/	/	
(Roh et al., 2023)	Finance technology	AI-enabled robo-advisors	No	+AT	+AT	+AT	+AT	/	/	Trust: +BI Perceived privacy: +BI, +FC, +Trust Perceived security: +Trust

(*continued*)

Table 1. Continued.

	Settings			UTAUT&UTAUT2 factorsa					Additional factors	
	Application contexts	Types of AI tools	GenAI or not	PE	EE	SI	FC	Other factors	Risk-related factors	Other factors
(Foroughi et al., 2023)	Education (adopted by students)	ChatGPT	Yes	+BI	+BI	+BI	+BI	HM: +BI Habit: +BI	/	Learning value: +BI
(An et al., 2023)	Language learning (adopted by junior and senior high students)	AI-assisted language learning systems	No	+BI (for junior high)	+BI (for junior high)	+BI (for senior high)		/	/	Learning experience with AI: +BI (for senior high) Cultural interest with AI: +BI Instrumentality-promotion with AI: +BI
(Strzelecki, 2023)	Higher education (adopted by students)	ChatGPT	Yes	+BI	+BI	+BI	+UB	HM: +BI PV: +BI Habit: +BI, +UB	/	Personal innovativeness: +BI
(Li, 2024)	Design activities (mainly adopted by students)	AI drawing tools	Yes	+BI	/	+BI	/	/	Perceived risk: -BI	Perceived anxiety: −EE

[a]PE refers to performance expectancy. EE refers to effort expectancy. SI refers to social influence. FC refers to facilitating conditions. HM refers to hedonic motivation. PV refers to price value.
[b]BI refers to behavioral intention. AT refers to attitude. UB refers to use behavior.
[c]"+" and "−" respectively refers to a positive influence and a negative influence.

2023), whereas some other studies treated trust as a consequent of PE and other perception factors (Kraus et al., 2023; Shamszare & Choudhury, 2023). On the contrary, perceived risk is much simpler. In addition, due to the strong association between perceived risk and trust, most previous studies applying UTAUT models for GenAI adoption included only one of them as shown in Table 1.

Besides these factors of users' perceptions, individual differences and personal traits have also been found to affect behavioral intention and user attitudes to GenAI. These differences include educational and professional background, technology fear (Cabrera-Sánchez et al., 2021), personal innovativeness (Foroughi et al., 2023; Gansser & Reich, 2021; García De Blanes Sebastián et al., 2022), and AI-related differences such as prior experiences with AI (Romero-Rodríguez et al., 2023; Yin et al., 2023) and AI anxiety (Yin et al., 2023).

A most frequently studied personal characteristic is personal innovativeness. It is defined as the willingness to try out new information technologies (Agarwal & Prasad, 1998) and has been found to increase the intention to use AI (García De Blanes Sebastián et al., 2022; Strzelecki, 2023). This definition denotes both dispositional traits (e.g., openness personality) as well as their characteristics of using information technologies. To distinguish the effects of general personality traits and technology-related characteristics, this study considered openness to new experiences and AI self-efficacy as potential factors, which were both found strongly and positively associated with personal innovativeness in previous studies (Ali, 2019; Jokisch et al., 2020; Nov & Ye, 2008; Yesil & Sozbilir, 2013).

Openness reflects the extent to which people think in broad and deep ways and are willing to experiment (Dollinger, 2012). Openness is regarded as the most salient personality dimension to predict the inclination toward innovation by researchers (Patterson et al., 2009), and many empirical studies revealed the correlation between openness and innovation (Ali, 2019; Batey & Furnham, 2006). Studies have suggested positive associations of openness with acceptance of AI (Sindermann et al., 2022) and perceived AI functionality (Park & Woo, 2022). However, it has not been included in UTAUT-based GenAI research.

AI self-efficacy can be defined as individuals' general confidence in their ability to use and interact with AI (Saville & Foster, 2021; Wang & Chuang, 2023) and was found to increase the intention to adopt AI technologies in daily contexts (Hong, 2022). Similarly, general technology self-efficacy or computer self-efficacy is also one of the most critical determinants of technology use (Ulfert-Blank & Schmidt, 2022) and has been found to increase the acceptance of technologies in various contexts (Celik & Yesilyurt, 2013; Yeşilyurt et al., 2016). However, few studies have explored how AI self-efficacy contributes to the adoption of GenAI in NPD.

2.3. Factors from the perspective of human-AI collaboration

Increasing NPD teams perceive AI as a team member instead of just a tool, and thus their adoption of AI can be influenced by the ways of human-AI collaboration, including AI's roles (or function allocation), autonomy, and communication styles. First, AI can be designed with various team roles, such as coordinator, creator, perfectionist, or doer (Siemon, 2022). Humans tend to have more positive attitudes toward AI teammates with similar traits and complementary skills such as analytical thinking or coordination (Lee & Nass, 2003). Second, AI can passively contribute when team members request or actively contribute with higher autonomy. AI with higher autonomy is more likely to be perceived as a team member and can foster positive human attitudes (Nass et al., 1996; Ulfert et al., 2023). Third, AI can communicate in different styles, manifested through explainability, information presentation, and language use. Users generally prefer a communication style that is clear, transparent, and visible for output (Ribera & Lapedriza García, 2019; Shin, 2021), with precise information format (Kim et al., 2021). In addition, the preferred language style may depend on the context of use, such as a preference for informal and abstract language styles in hedonic-dominant service contexts (Liebrecht et al., 2021; Lan et al., 2024).

All these design features in human-AI collaboration influence the extent to which users perceive AI as a team member and can be described as perceived anthropomorphism (PA). Although GenAI tools like ChatGPT are not designed to mimic humans, users often perceive them to behave like humans, especially in text-based interactions (Kim et al., 2024; Zamfirescu-Pereira et al., 2023). Previous studies on chatbots have revealed that anthropomorphism can be determined by observable features like appearance, and communication behaviors including verbal and non-verbal cues (Janson, 2023; Li & Suh, 2022; Seeger et al., 2021; Van Pinxteren et al., 2020). People perceive higher anthropomorphism when AI has abilities to provide tailored responses (Schuetzler et al., 2020) in communication styles with informal languages and emotional cues (Araujo, 2018) including empathy (Pelau et al., 2021) and humor (Moussawi & Benbunan-Fich, 2021). These findings of chatbots are also applicable to GenAI tools. For instance, ChatGPT outputs content with verbal cues like emotional tones and linguistic styles. Moreover, the outputs are presented word by word, resembling the human typing process, serving as a non-verbal cue. Research indicates that perceived anthropomorphism can create psychological bonding with humans (Li & Sung, 2021), build trust (Cheng et al., 2022; Glikson & Woolley, 2020), engage human participation (Fakhimi et al., 2023), enhance perceived usefulness (Blut et al., 2021; Rietz et al., 2019), and further improve user acceptance.

3. Framework

Despite the rapid growth of GenAI use in the NPD contexts, it remains unexplored what factors are associated with teams' attitudes and intentions to use GenAI specifically for NPD purposes. While UTAUT has been applied to study GenAI adoption in other contexts, it has not addressed unique aspects of NPD. During the NPD process, teams increasingly anthropomorphize GenAI, which can influence perceived effectiveness and attitudes but has been overlooked in UTAUT-based GenAI adoption studies. Moreover, the compatibility of GenAI and NPD's multifaceted tasks has not been linked to teams' attitudes or intentions to use GenAI. Therefore, we propose a research question: What factors influence team members' attitudes and intentions to use GenAI in new product development?

We conducted two studies to answer the research question, including an interview study and a questionnaire study as shown in Figure 1. The sequence of the two studies followed "exploratory sequential," which means qualitative research followed by quantitative research (Creswell &

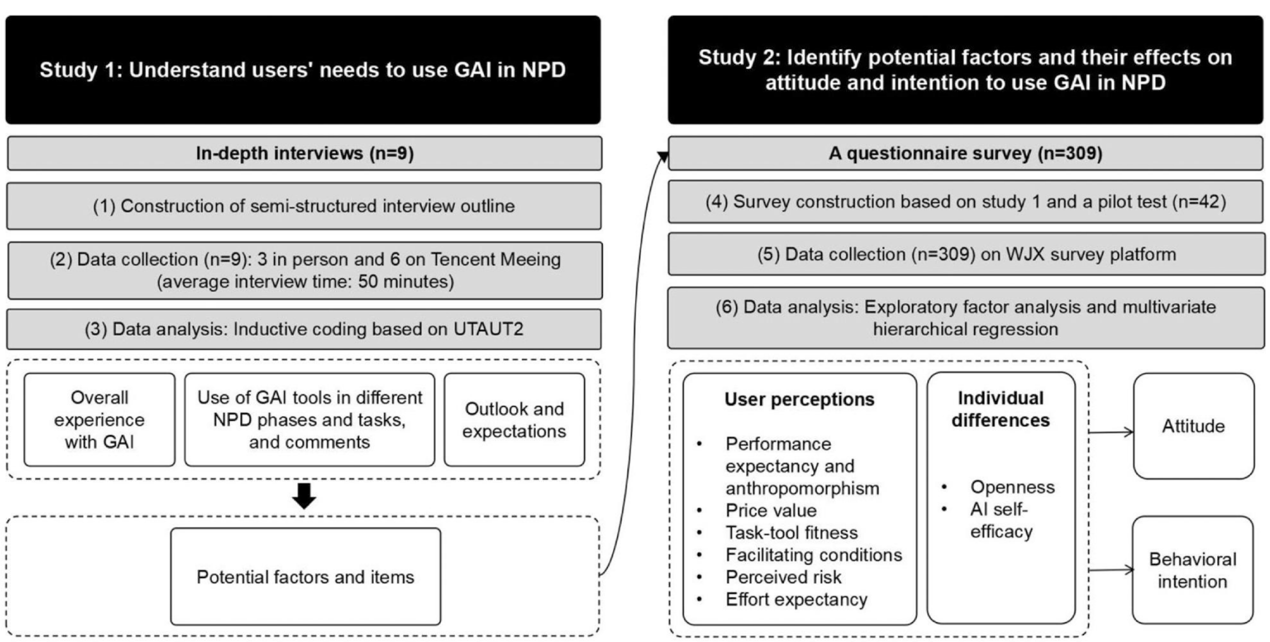

Figure 1. Roadmap of this study.

Clark, 2007; Shorten & Smith, 2017). Study 1 aimed to qualitatively understand the potential factors related to users' adoption of GenAI tools in NPD through in-depth interviews. We asked about their experiences, difficulties, and expectations about adopting GenAI in NPD-related activities. Study 2 aimed to quantitatively identify the factors significantly associated with the attitudes towards and intentions to use GenAI tools. The questionnaire was designed based on interviews in Study 1 and UTAUT literature. The data was analyzed by exploratory factor analysis along with hierarchical regression analysis to determine the contributions of potential factors.

4. Study 1: Interviews

Study 1 aims to determine the alternative factors and items for constructing the UTAUT model later in Study 2 as well as providing a comprehensive understanding of how teams use current generative AI tools for new product development. To do so, we conducted in-depth individual interviews with nine participants who used GenAI tools for product development or creative purposes.

4.1. Method

4.1.1. Participants

We recruited participants through two channels: (1) recruiting from the researchers' social network, and (2) sending targeted advertisements to social media influencers who created professional AI-related content. Each participant utilized at least one GenAI tool to assist in their work related to new product development or content creation. Among the nine participants, 7 were female and 2 were male, aged between 22 and 45 ($M = 28.38$, $SD = 6.87$). All participants had a bachelor's degree or above. As shown in Table 2, the participants included design students and professors in universities, professional designers, programmers, user researchers from different industries, and AI-generated content bloggers on social media. We interviewed users from diverse backgrounds to obtain a more comprehensive understanding and an extensive item pool of the questionnaire in Study 2.

4.1.2. Procedure

We conducted individual semi-structured interviews with each participant and discussed questions in the following aspects: (1) overall experience with GenAI (e.g., "How did you come to know about GenAI tools?"), (2) their use of GenAI tools in different NPD phases and tasks (e.g., "What tasks do you typically use GenAI tools to assist with?"), (3) their comments on the effectiveness of GenAI tools (e.g., "What kind of assistance do GenAI tools provide in this task?"), and (4) outlook and expectations (e.g., "What additional functionalities do you hope to see in future GenAI tools?") as shown in Appendix.

The interviews were conducted in April and May 2023. Three participants were interviewed in person in a quiet room, whereas others were interviewed online via Tencent Meeting. Each interview lasted about 50 minutes. All interviews were audio recorded and transcribed later. The transcribed data was later coded with NVivo 11.0. To obtain the questionnaire item pool, we coded the data by a hybrid approach of deductive and inductive coding. We adopted the factors in the UTAUT2 framework, but also inductively generated new factors identified from the interviews.

4.2. Results

4.2.1. Overall use and experience

Seven respondents became aware of GenAI tools between late 2022 and early 2023 through various sources, including news, social media, professional networks, and conversations with classmates and friends. They attempted to start using GenAI tools in early 2023. The other two participants (P6 and P9) had more prior experience using GenAI tools to assist with their work from the end of 2022.

All participants used ChatGPT, which was also the most frequently used text-based AI tool among them. In addition, four participants also used Ernie Bot and New Bing. In the early stages before development, they used text-based GenAI tools to gain knowledge and information (P1, P2, P3, P4, P5, and P7), seek inspiration (P1, P3, and P5), and establish initial design frameworks (P1). In addition, some participants also used text-based GenAI tools to write codes (P4, P8, P9), translate languages (P1, P2, P3, P9), and generate content (P2 and P7).

Design students and professionals also used image-based GenAI tools, including Midjourney (P1, P3, P6, P7), Wenxin Yige (P1, P2, P3), and Stable Diffusion (P7). They used image-based AI tools for design inspirations during the early stages (P1, P3) and to obtain more specific design references during the development stage (P3, P5, P6, and

Table 2. Background information of participants in Study 1.

ID	Age	Gender	Education	Occupation	Frequency of using GenAI tools
P1	22	Female	Bachelor	Design student (industrial design)	More than once a week
P2	22	Female	Bachelor	Design student (product design and user experience)	Multiple times a day
P3	23	Female	Bachelor	Design student (visual communication)	More than once a week
P4	31	Female	PhD	User researcher (with 2.5 years of work experience)	Irregular frequency
P5	45	Female	Master	Associate professor of civil engineering	Once or twice a month
P6	29	Female	Bachelor	Freelance designer and blogger (with 7 years of experience in UI design, graphic design, and visual design)	Multiple times a day
P7	25	Male	Bachelor	Architectural designer (public building design and urban planning with 3 years of work experience)	Multiple times a day
P8	27	Male	Master	Programmer (working in a well-known IT company)	About once a week
P9	25	Female	Bachelor	Game system designer (with 3 years of work experience)	Once or twice a month

P7). They also used these tools to generate concept images for effective communication among respondents, clients, and team members (P7). These generated initial design works or elements could be further refined, modified, and even directly incorporated into the final design (P6).

4.2.2. Potential factors

Most perceptional factors in UTAUT2 were mentioned by participants, including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and price value. Participants also mentioned perceived risk.

4.2.2.1. Performance expectancy. All the participants suggested that their acceptance could be strongly affected by three aspects of the performance of GenAI tools: functionality, output performance, and contribution to their work. First, the participants emphasized functionality in customization and iterability. Customization allowed users to make specific settings or instructions to customize the output of GenAI, and iterability allowed users to iteratively adjust and improve the output to better meet their expectations. For example, when using image-based GenAI tools, users used prompts to set rendering style, perspective, and composition (P1). However, due to some technological limitations of the current GenAI (P3 and P7), these settings did not always meet users' expectations. It was also hard for users to make some detailed adjustments (P6 and P7). Overall, users' perception of the functionality strongly affected their acceptance.

Second, output performance meant how users perceived that GenAI outputted high-quality content that met users' expectations. The participants expected the generated content to be accurate, professional, logically sound, creative, and aesthetically pleasing (for image-based GenAI). Regarding accuracy and logic, the participants agreed that the current GenAI tools had high accuracy in translation, summarization, and template-based document generation (P2, P9), and code-writing (P8), but these tools sometimes fabricated fake information (P4, P5, and P9). In addition, GenAI tools generated text in an organized manner (P1), but the actual logical coherence between sentences and paragraphs was weak (P4 and P5), and occasional logical errors occurred (P8). Overall, they found that GenAI tools performed well in answering questions about daily life but were lacking in solving professional problems (P2 and P4). Regarding the creativity of output performance, the generated images were often inspirative (P1) with the introduction of unexpected content (P6). The pictures generated by AI were also regarded as aesthetically pleasing and exquisitely crafted (mentioned by most participants). However, current GenAI tools performed worse in idea-generation tasks with specific requirements and even provided outdated ideas in some cases (P1 and P3).

Third, the participants also evaluated the contribution of GenAI to their work. All of them suggested a major motivation to use GenAI tools is to improve working efficiency. P4 used GenAI tools to quickly gather and summarize a large amount of information and summarize it concisely. P7 used AI tools to generate many high-quality images for references for design in a short period. GenAI tools also enabled UI designers to quickly create high-fidelity prototypes (P6), making them more competitive in their workplace (P5 and P7).

4.2.2.2. Effort expectancy. Most participants mentioned effort expectancy in both interaction modes and usability. Users required clear, understandable, and user-friendly ways to interact with GenAI. Most participants preferred text-based interactions, such as dialogues and keyword prompts. In addition, some participants also expressed a need for more diverse modes, such as voice interactions, file uploads, and image recognition, as well as functions for tracking previous interactions and automatic saving or synchronization.

Regarding usability, users sought an easy-to-learn, language barrier-free, and fast and efficient usage experience. All the participants said that the current GenAI tools were user-friendly and efficient, though some output content required further debugging or modifying (P1, P2, and P7). They considered GenAI tools, especially text-based ones (P9), easier to learn than many traditional design-assistant tools. Some participants said they perceived some language barriers because most GenAI tools were designed in English whereas the first language of the participants was Chinese (P1, P6, and P7). However, the language barriers did not hinder the participants' usage.

4.2.2.3. Social influence. All participants mentioned that using GenAI tools was a social trend in today's society, and this perception contributed to their acceptance of GenAI tools. Participants were inclined to use the GenAI tool due to its widespread recognition (P1, P5, and P9), favorable social reputation (P1 and P3), and frequent usage and discussions among their peers (P5, P6, P8). For instance, P1 was motivated to use a GenAI tool as she frequently encountered related content on social media platforms, accompanied by numerous positive reviews. In addition, P7 expressed a fear of being left behind and that people who could not use GenAI tools at work would be eliminated from their jobs.

4.2.2.4. Facilitating conditions. Many participants mentioned challenges in conditions, including IP addresses, and software or hardware requirements. Due to IP address restrictions, most interviewees need to use other auxiliary tools to successfully access GenAI tools. P7 mentioned that some image-based GenAI tools had very high hardware requirements, which could hinder some potential users from adopting the tools. In addition, facilitating conditions in UTAUT usually included knowledge acquisition and the accessibility of supportive information. Our participants found the current GenAI tools performed well in these aspects. They found GenAI tools easy to learn, and they could easily obtain supportive information online because of the good atmosphere of sharing among GenAI user communities in China (P6, P7).

4.2.2.5. Hedonic motivation. Although not widely mentioned, three participants (P6, P7, and P9) reported being influenced by hedonic motivation when utilizing GenAI for new product development. Initially driven by curiosity (P7, P9), they found the interaction with GenAI to be engaging and interesting. For P6 and P7, it became more than just a tool for work but developed into a personal interest, leading them to various new experiences. P6 and P7 were both expert users, indicating that hedonic motivation may be positively related to attitude, behavioral intention, and use behavior.

4.2.2.6. Price value. Student participants especially considered free availability when selecting a GenAI tool for NPD-related activities. Additionally, the interviews revealed that in a commercial setting, users were more willing to accept relatively high prices as long as the effectiveness worthed the price.

4.2.2.7. Perceived risk. Participants also mentioned potential risks that potentially reduced their intention to use, including privacy, dependency, job loss, and copyright issues. First, participants worried that GenAI tools could infringe upon their privacy rights as these tools required large amounts of personal data (P4). Second, some participants also worried that they would lose their professional skills and abilities over time if they relied too much on GenAI tools (P3 and P5). It could further reduce their work efficiency and innovation potential. Third, from a scope of the society, P1, P3, P5, P6, and P7 worried that the widespread use of GenAI technology could result in a significant reduction in job opportunities and increase unemployment rates. Fourth, P1, P2, P3, and P9 worried about copyright issues due to the lack of clear regulations on the copyright of GenAI works. They also worried that their works might be used without permission, or the content they generated was not commercially viable. It is worth noting that such concerns did not necessarily hinder usage, especially for expert users. P6 and P7 as expert users expressed that these concerns about risks sparked their curiosity, prompting them to try and use GenAI tools more.

4.2.3. Expectations for future GenAI tools

Participants also expressed their expectations for future GenAI tools. They expected text-based GenAI tools could understand emotional and cultural content (P4 and P8), provide rich interactive modes (P1 and P9), and proactively assist with the tasks (P4 and P9). They expected image-based GenAI tools more powerful in functions such as font design (P6) and 3D modeling (P1 and P6) to assist designers. Besides, participants hoped that GenAI tools would evolve beyond a standalone tool and instead be plugins and integrated with other tools (such as the GPTs in 2024), embedding GenAI capabilities across various professional domains (P4). They also expressed the desire for GenAI tools to be able to evaluate human performance (P1).

5. Study 2: Survey to identify factors

5.1. Method

5.1.1. Participants

To investigate which factors influence team members' attitudes and intentions to use GenAI tools in new product development, we conducted an online survey. We used WJX Survey Platform to distribute the questionnaire and collect data. The link to the questionnaire was distributed via WeChat and Weibo in July 2023. The screening criteria required participants to have occupations related to NPD or study in relevant majors and have experience using GenAI tools to support their tasks relevant to new product development. We followed guidelines recommending a minimum sample size of 300 (e.g., Comrey & Lee, 1992; Tabachnick & Fidell, 2007). In total, 349 questionnaires were returned, and 309 of them were valid. After conducting the regression analysis, we used G*Power to conduct power analysis and verified that the recommended sample size for our regression models to obtain sufficient power (0.8) is 243, which was less than our actual sample size of 309.

Fifty-two percent of participants were males, whereas 48% were females. Participants aged from 18 to 46 years ($M = 25.25$, $SD = 4.53$). Sixty-four percent of them were working professionals. Most participants ($N = 285$, 92%) either had a bachelor's degree or higher or were current undergraduate students. Among all industries, participants working or studying in Information Technology (IT) constituted the largest proportion at 34% ($N = 105$), followed by culture, sports, and entertainment ($N = 44$, 14%), education ($N = 32$, 10%), and scientific research and technical services ($N = 26$, 8%).

5.1.2. Questionnaire design and data analysis

Before the formal study, we conducted a pilot survey with 42 GenAI users and adjusted the questionnaire design to ensure that the final released questionnaire would be accurately understood by the participants. In the formal version of the questionnaire, participants were asked to complete it based on a GenAI tool they used most frequently in their recent NPD work.

The questionnaire consisted of five sections. The first section asked the participants to check whether they met the recruitment criteria and to self-report several behavioral data. First, the participant was asked to confirm her/his experience of using GenAI tools and to answer a multiple-choice question to select whether they had used text-based and image-based GenAI tools. To help participants' understanding, this question gave examples for each option (ChatGPT, New Bing, Jasper AI, and Ernie Bot for text-based tools; Midjourney, Stable Diffusion, Autodraw, and Wenxin Yige for image-based tools). Second, the participant was asked to select her/his tasks in NPD by a multiple-choice question with seven options, namely project management, design, development and engineering, user research, marketing and promotion, content production, and others. Third, the participant was asked to choose one of the GenAI tools she or he used most frequently in the recent NPD work and fill in the rest of the questionnaire based on this GenAI tool. She/he was asked to choose whether this GenAI tool was text-based or image-based and to estimate the frequency of using the selected GenAI tool. This frequency of use was measured by a single item with five levels scored from 1 to 5 (ie, "once a month or less," "several times per month," "once or twice per week," "several times per week," and "every day").

In the second section, the participants were asked to rate their perceptions of the GenAI tool on a 43-item 5-point Likert scale. We integrated both items emerging from the interviews and the items from the UTAUT2 questionnaire (Venkatesh et al., 2012) to describe performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation, price value, perceived risk, and perceived anthropomorphism. Note that in previous UTAUT questionnaires, perceived risk is usually measured by items about finance, function, society, and other dimensions from perceived risk theory (Bettman, 1973; Stone & Grønhaug, 1993). However, these items did not overlap with the risks mentioned in the interviews of Study 1. Therefore, we extracted 5 items from the interviews to measure perceived risk. In addition, this section also added perceived anthropomorphism as a potential factor, which was measured by the 4 items from the Godspeed I questionnaire (Bartneck et al., 2009). We removed one item from the original questionnaire because it was related to the movement of the robot.

In the third section, the participants were asked about their attitudes and behavioral intentions of using GenAI tools in new product development. The participant's attitude was measured by a 2-item 9-point Likert scale rating of GenAI tools in terms of UI and functionality for new product development. The behavioral intention was measured by a 3-item 5-point Likert scale adapted from the UTAUT2 questionnaire (Venkatesh et al., 2012).

The fourth section measured the individual differences in openness to new experiences and AI self-efficacy. Openness was measured by a 2-item 7-point scale from the Ten-Item Personality Inventory (TIPI) (Gosling et al., 2003). AI self-efficacy was measured using a 5-item 9-point scale from the Internet Self-efficacy Survey (ISS) (Chuang et al., 2015). We replaced the term "Internet" with "GenAI tools" in each item in the original ISS to align them with the context of our study.

In the last section, participants were requested to provide their demographic information, including age, gender, educational background, and industry (or profession for students). The educational background had five levels scaled from 1 to 5 representing junior high school, senior high school/vocational school, junior college, bachelor's, and master's or above. The 20 options of industry were adopted from the classification of the Industrial Classification for National Economic Activities (AQSIQ & SAC, 2017).

To enhance data validity, the questionnaire includes an attention-check question asking participants to select "very agree." The response selecting other options in this question would be considered invalid. Additionally, we used the response durations as a criterion for screening valid responses. Based on the pilot test, responses within 2 min were considered invalid.

Regarding data analysis, we first conducted an exploratory factor analysis to identify the final set of items and the factors. Then, we employed hierarchical regression analysis to identify the factors that significantly influenced attitudes and behavioral intentions. Independent variables were divided into three groups: demographic variables (age, gender, and education), individual differences (AI self-efficacy and openness to new experiences), and perceptional factors (anthropomorphism and the factors from UTAUT). These independent variables were gradually added into the models, and the increased R squared could reflect the significance of contribution by each group of independent variables. In addition, we calculated effect sizes for the factors that we focused on in Stage 3, using the measure of Cohen's f^2 (Selya et al., 2012).

5.2. Results

5.2.1. Overall attitude, behavioral intention, and frequency of use by participants in different backgrounds

Before identifying the potential factors, we summarized descriptive statistics for attitude, intention to use, and self-reported frequency of use for participants in different backgrounds as shown in Table 3.

5.2.1.1. Demographic background. Our data showed that males had better attitudes to GenAI and higher frequencies of use (p values <0.001 by one-way ANOVA). Later in the third stage of hierarchical regression, gender was not a significant predictor, indicating no gender differences after controlling other factors such as the perception factors in the UTAUT framework. Participants from different educational backgrounds had no significant difference in attitude, intention, and frequency of use.

5.2.1.2. GenAI experience. Most of our participants had the experience of using text-based tools ($N = 288$). As shown in Figure 2, participants who had used both text-based and image-based tools reported significantly higher frequency of use ($\chi^2_2 = 23.10$, $p < 0.001$ by Kruskal-Wallis test).

5.2.1.3. Industry and tasks in NPD. The participants were asked to select their industry from 20 options. The results showed that four options were chosen by much more participants than others, namely information technology (IT, $N = 105$, 34%), culture, sports, and entertainment ($N = 44$, 14%), education ($N = 32$, 10%), and scientific research and technical services ($N = 26$, 8%). Frequency of use significantly differed among industries ($\chi^2_4 = 24.10$, $p < 0.001$ by Kruskal–Wallis test). Post-hoc analysis (pairwise Wilcoxon Rank Sum Test with Bonferroni correction) suggested that participants in the IT industry reported higher frequencies of use ($M = 3.60$, $SD = 1.01$) than those in the education industry ($M = 2.66$, $SD = 1.07$, $p < 0.001$) and others ($M = 3.04$, $SD = 1.13$). Participants in the industry of scientific research and technical services also reported higher

Table 3. Means and standard deviations of attitude, intention to use, and self-reported frequency of use.

	N	Attitude (1–9)	Intention (1–5)	Frequency (1–5)[a]
Gender				
Female	147	7.13 (1.15)	4.29 (0.59)	3.10 (1.19)
Male	162	7.65 (1.08)	4.30 (0.54)	3.45 (1.08)
Education				
Junior college or lower	24	7.33 (1.41)	4.15 (0.55)	3.50 (1.18)
Bachelor's	197	7.55 (1.11)	4.33 (0.47)	3.30 (1.13)
Master's or higher	88	7.09 (1.08)	4.27 (0.72)	3.18 (1.16)
GenAI experience				
Text-based only	167	7.45 (1.53)	4.24 (0.61)	3.19 (1.17)
Image-based only	21	7.38 (1.06)	4.25 (0.55)	3.02 (1.07)
Both text- and image-based	121	7.43 (1.18)	4.37 (0.57)	3.67 (1.13)
Industry				
IT	105	7.37 (1.11)	4.28 (0.54)	3.60 (1.01)
Culture, sports, and entertainment	44	7.12 (1.13)	4.21 (0.73)	3.39 (1.30)
Education	32	7.30 (0.99)	4.39 (0.49)	2.66 (1.07)
Scientific research and technical services	26	7.50 (1.10)	4.46 (0.52)	3.58 (1.06)
Others	102	7.57 (1.22)	4.28 (0.52)	3.04 (1.13)
Tasks in NPD[b]				
Project management	76	7.41 (1.40)	4.36 (0.55)	3.32 (1.10)
Design	149	7.54 (1.18)	4.31 (0.57)	3.44 (1.15)
Development and engineering	94	7.59 (1.20)	4.30 (0.53)	3.56 (0.99)
User research	90	7.61 (1.03)	4.32 (0.58)	3.20 (1.06)
Marketing and promotion	93	7.41 (1.19)	4.23 (0.52)	3.13 (1.06)
Content production	84	7.59 (1.20)	4.30 (0.53)	3.56 (0.99)
Types of GenAI tools to answer the questionnaire				
Text-based	238	7.44 (1.07)	4.30 (0.53)	3.25 (1.13)
Image-based	71	7.27 (1.35)	4.28 (0.65)	3.39 (1.19)

[a]Frequency from 1 to 5: "once a month or less," "several times per month," "once or twice per week," "several times per week," and "every day."
[b]Participants could select multiple options of tasks in NPD. Only 2 participants selected "others" in this question, and therefore they were not included in this table.

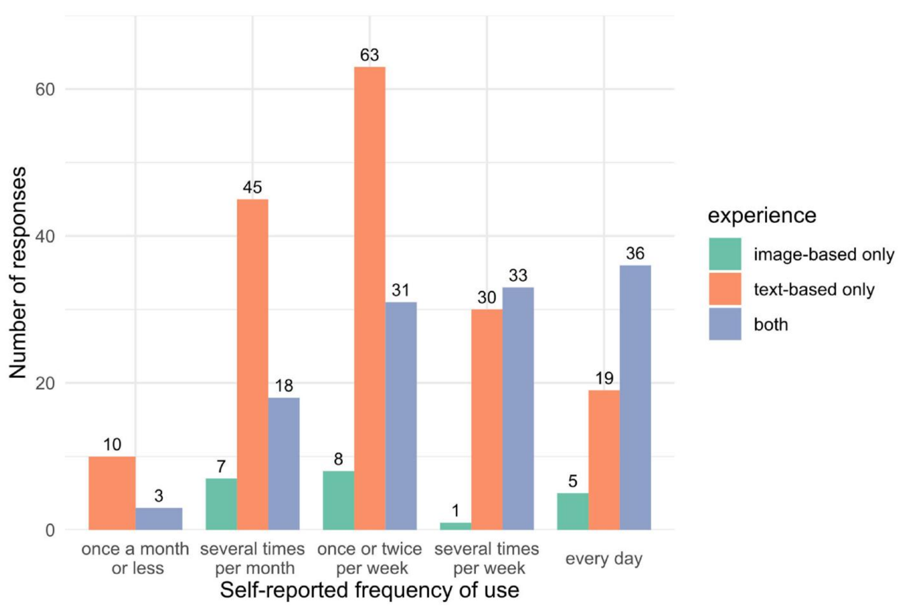

Figure 2. Histogram for frequency of use reported by participants with different GenAI experience.

frequencies of use ($M = 3.58$, $SD = 1.06$) than those in the education industry ($M = 2.66$, $SD = 1.07$, $p = 0.03$).

Among the tasks in NPD, the design was selected by nearly half of the participants ($N = 149$, 48%). The distribution of other tasks was relatively even. Each task was selected by approximately one-third of the participants. Over half of the participants ($N = 175$, 57%) selected more than one task. We also descriptively summarized the tasks selected by people from different industries as shown in Figure 3. Unsurprisingly, IT professionals took on more development tasks, whereas those in cultural and educational fields did more content creation and user research. Moreover, participants with experiences in design, development, and user research reported more positive attitudes and higher frequencies of use. Participants engaging in design tasks reported more positive attitudes ($M = 7.54$, $SD = 1.18$) and higher frequencies of use ($M = 3.44$, $SD = 1.15$) than other participants ($M = 7.28$, $SD = 1.09$,

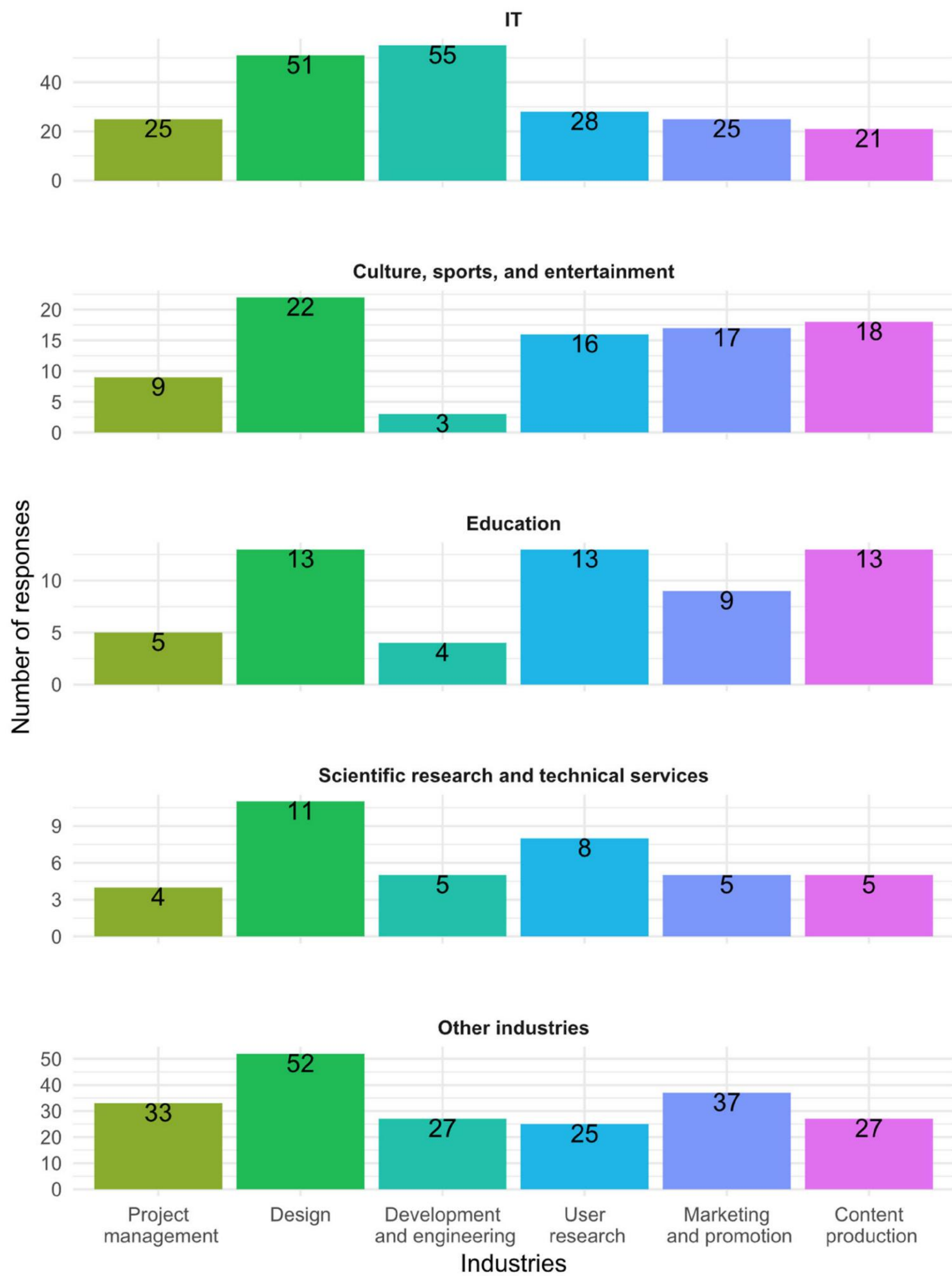

Figure 3. Background information: the NPD-related tasks of participants in different industries.

$F_{1,\ 307} = 3.99$, $p = 0.047$ by ANOVA for attitudes; $M = 3.14$, $SD = 1.12$, $\chi^2_1 = 6.00$, $p = 0.01$ by the Kruskal–Wallis test for frequencies). Participants engaging in development tasks reported higher frequencies of use ($M = 3.56$, $SD = 0.99$) than other participants ($M = 3.16$, $SD = 1.18$, $\chi^2_1 = 8.27$, $p = 0.004$ by the Kruskal–Wallis test). Participants engaging in user-research tasks reported better attitudes ($M = 7.61$, $SD = 1.03$) than other participants ($M = 7.32$, $SD = 1.18$, $F_{1,\ 307} = 4.26$, $p = 0.04$ by ANOVA).

5.2.1.4. Type of selected GenAI tools to answer the questionnaire. Most participants chose a text-based tool ($N = 238$). No significant difference in attitude, intention, or frequency of use was found between the two types of selected tools.

5.2.2. Exploratory factor analysis of GenAI user perception in new product development

We conducted an exploratory factor analysis to identify the major dimensions of users' perception of GenAI in the new product development context. To ensure the data was feasible for factor analysis, we conducted the Kaiser–Meyer-Olkin (KMO) test and Bartlett's test of sphericity. The results showed that the KMO measure was 0.91 (with $p < 0.001$ and above the commonly recommended value of 0.60), and the sphericity was significant ($\chi^2 = 6189.2$, $p < 0.001$), indicating our data was feasible for factor analysis.

We conducted a principal component factor analysis with varimax rotation on the 43 perception items. We dropped 19 items that either did not strongly load on any factor

Table 4. Factor loadings (principal components, varimax rotation).

	Item	*M*	*SD*	Loading
Factor 1: Performance Expectancy and Anthropomorphism, alpha = 0.85, *M* = 3.63, *SD* = 0.75.				
1	I feel that the GenAI tool is conscious, rather than just being an unconscious machine. (PA 3)	3.40	1.16	0.79
2	I feel that the GenAI tool is lifelike and not artificial. (PA 4)	3.42	1.10	0.79
3	The GenAI tool outputs authentic and trustworthy content. (PE7)	3.52	0.97	0.78
4	The GenAI tool outputs accurate content. (PE 8)	3.59	0.93	0.73
5	The GenAI tool outputs highly professional content. (PE 5)	3.90	0.87	0.62
6	The GenAI tool outputs creative content. (PE 9)	3.95	0.87	0.62
Factor 2: Perceived Risk, alpha = 0.86, *M* = 3.58, *SD* = 0.93.				
1	I have privacy concerns when using the GenAI tool. (PR 3)	3.66	1.12	0.83
2	I am concerned that using the GenAI tool may bring risks to my work and life. (PR 1)	3.41	1.19	0.83
3	I am concerned about copyright issues when using the GenAI tool. (PR 2)	3.61	1.12	0.82
4	I am concerned that the development of the GenAI tool may reduce job opportunities in my industry. (PR 5)	3.57	1.21	0.77
5	I am concerned that using the GenAI tool may make me too reliant on it. (PR 4)	3.62	1.13	0.77
Factor 3: Task-Tool Fitness, alpha = 0.77, *M* = 4.26, *SD* = 0.51.				
1	I find the GenAI tool useful for my work. (PE 1)	4.28	0.65	0.83
2	Using GenAI tools is a trend in today's society. (SI 1)	4.32	0.67	0.83
3	I find the AI tool easy to use. (EE 3)	4.23	0.73	0.82
4	Using GenAI tools has improved my work efficiency. (PE 4)	4.31	0.68	0.77
Factor 4: Facilitating Condition, alpha = 0.75, *M* = 4.15, *SD* = 0.58.				
1	I have the necessary hardware and software to successfully use the GenAI tool. (FC 3)	4.16	0.73	0.75
2	I can easily access resources and information related to the GenAI tool, such as tutorials, materials, models, and communities of like-minded individuals. (FC 4)	4.05	0.77	0.73
3	I have the resources necessary to use the GenAI tool. (FC 1)	4.23	0.65	0.68
Factor 5: Price Value, alpha = 0.77, *M* = 3.98, *SD* = 0.71.				
1	At the current price, the GenAI tool provides a good value. (PV 3)	4.05	0.88	0.80
2	The GenAI tool is reasonably priced. (PV 1)	3.90	0.88	0.75
3	The GenAI tool is a good value for the money. (PV 2)	4.00	0.81	0.63
Factor 6: Effort Expectancy, alpha = 0.73, *M* = 4.13, *SD* = 0.61.				
1	Learning how to use the GenAI tool is easy for me. (EE 1)	4.13	0.78	0.80
2	My interaction with the GenAI tool is clear and understandable. (EE 2)	4.31	0.68	0.73
3	Using the GenAI tool is a convenient and efficient process that does not require a significant amount of time. (EE 4)	4.16	0.76	0.58

(loading < 0.5) or exhibited similar values of loading on two factors (loading > 0.4). Finally, 24 items remained as shown in Table 4. A six-factor structure merged with no cross-loading above 0.4. Altogether, 65% of the total variance was explained by the five factors, indicating a good fit of the model. The Cronbach's alpha coefficients for the six factors were 0.85, 0.86, 0.77, 0.75, 077, and 0.73, respectively, all above the threshold of 0.60 suggested for exploratory search (Hair, 2009).

Factor 1, labeled as performance expectancy and anthropomorphism, consisted of six items and explains 15% of the total variance. It covered both output performance expectancy (e.g., "The GenAI tool outputs authentic and trustworthy content") and anthropomorphism perceptions (e.g., "I feel that the GenAI tool is conscious, rather than just being an unconscious machine"). Factor 2, labeled as perceived risk, explained 14% of the total variance. It consisted of five items related to the perception of potential risks and threats, such as privacy concerns and copyright concerns. Factor 3, labeled as task-tool fitness, explained 11% of the total variance. It comprised four items related to the perception that GenAI tools were suitable for the task, including their usefulness, efficiency, ease of use, and alignment with social trends. Overall, it describes a perception that the GenAI tool is compatible with users' tasks related to new product development. Factor 4, labeled as facilitating conditions, explains 9% of the total variance. It consisted of three items describing the situational or environmental elements that supported users to use GenAI tools in new product development (e.g., easy access to resources and information). Factor 5, labeled as price value, explained 8% of the total variance and involved three items about the cost-effectiveness of GenAI (e.g., being reasonably priced). Factor 6, labeled as effort expectancy, accounts for 8% of the overall variation and relates to the level of user effort required (e.g., being easy to learn and use).

5.2.3. Hierarchical regressions to predict attitudes and behavioral intentions

We conducted two hierarchical multiple regression analyses to examine the contribution of the above-identified perception factors as well as individual differences in explaining the attitude and intention to use GenAI tools in new product development. Before regressions, we conducted preliminary analyses to ensure no violation of assumptions of independence, singularity, and multicollinearity (all variance inflation factors < 1.7). In hierarchical regressions, age, gender, and education were initially included in the first stage to control the effects of demographic features. In the second stage, openness and AI self-efficacy were included in the model. The identified factors of user perception were included in the third stage. The results of the regression analyses are summarized in Table 5.

In the first stage, the control variables (gender, age, and education) explained 7% of the variance in the attitude toward GenAI utilization in NPD ($F_{3,305} = 7.70$, $p < 0.001$), but could not predict behavioral intention ($R^2 = 0.01$, $p = 0.584$). In the second stage, we found a significant increase of R^2 from the introduction of openness and AI

Table 5. Hierarchical regressions predicting the attitude and the behavioral intention to use GenAI tools in new product development.

	Attitude				Behavioral intention			
	ΔR^2	β	p value	Cohen's f^2	ΔR^2	β	p value	Cohen's f^2
Stage 1	0.07				0.01			
Intercept			<0.001***				<0.001***	
Age		0.107	0.064			0.076	0.203	
Gender		0.190	0.001**			−0.006	0.925	
Education		−0.122	0.035*			0.014	0.810	
Stage 2	0.16				0.13			
Intercept			<0.001				<0.001	
Age		0.071	0.183			0.024	0.667	
Gender		0.099	0.067			−0.055	0.337	
Education		−0.073	0.169			0.053	0.343	
AI Self-efficacy		0.412	<0.001***			0.293	<0.001***	
Openness		−0.009	0.869			0.191	0.001**	
Stage 3	0.10				0.35			
Intercept			<0.001***				<0.001***	
Age		0.038	0.471	0.001		0.020	0.663	0.002
Gender		0.083	0.111	0.008		−0.022	0.619	0.002
Education		0.006	0.916	<0.001		0.013	0.788	0.002
AI Self-efficacy		0.209	0.001**	0.051		−0.003	0.958	<0.001
Openness		−0.038	0.477	0.002		0.011	0.815	<0.001
Performance Expectancy and Anthropomorphism		0.298	<0.001***	0.092		0.094	0.060	0.012
Perceived Risk		0.024	0.632	<0.001		−0.023	0.604	<0.001
Task-Tool Fitness		0.125	0.015*	0.026		0.578	<0.001***	0.568
Facilitating Condition		0.075	0.150	0.006		0.210	<0.001***	0.073
Price Value		0.160	0.001**	0.034		0.231	<0.001***	0.097
Effort Expectancy		0.157	0.002**	0.031		0.215	<0.001***	0.079

Male—1, female—0.
*significant at 0.05 level.
**significant at 0.01 level.
***significant at 0.001 level.

self-efficacy including an additional 16% variance in attitude ($F_{2,303} = 17.65$, $p < 0.001$) and an additional 13% variance in behavioral intention ($F_{2.303} = 9.83$, $p < 0.001$).

In the third stage, the introduction of perception factors explained an additional 10% variance of the attitude ($R^2 = 0.33$, $F_{6,297} = 13.20$, $p < 0.001$) and 35% variance of the intention ($R^2 = 0.49$, $F_{6,297} = 26.25$, $p < 0.001$) to use GenAI tools in NPD. The final model of attitude showed that the prominent predictor was performance expectancy and anthropomorphism ($\beta = 0.298$, $p < 0.001$), followed by AI self-efficacy ($\beta = 0.209$, $p = 0.001$), price value ($\beta = 0.160$, $p = 0.001$), effort expectancy ($\beta = 0.157$, $p = 0.002$), and task-tool fitness ($\beta = 0.125$, $p = 0.015$). For behavioral intention, the strongest predictor was task-tool fitness ($\beta = 0.578$, $p < 0.001$), followed by price value ($\beta = 0.231$, $p < 0.001$), effort expectancy ($\beta = 0.215$, $p < 0.001$), and facilitating condition ($\beta = 0.210$, $p < 0.001$). In addition, performance expectancy and anthropomorphism showed a marginally significant impact on behavioral intention ($\beta = 0.094$, $p = 0.060$).

The results of Cohen's f^2 suggested that most of the significant predictors had small to medium effects. Similar to the results of the goodness of fit of models, predictors in the behavioral intention model had stronger effects than those in the attitude model. In the final attitude model, the factor of performance expectancy and anthropomorphism had the largest effect (Cohen's $f^2 = 0.092$), followed by AI self-efficacy (Cohen's $f^2 = 0.051$), price value (Cohen's $f^2 = 0.034$), effect expectancy (Cohen's $f^2 = 0.031$), and task-tool fitness (Cohen's $f^2 = 0.026$). In the final model of behavioral intention, task-tool fitness emerged as the most influential predictor, exhibited a large effect (Cohen's $f^2 = 0.568$), while facilitating condition (Cohen's $f^2 = 0.073$), price value (Cohen's $f^2 = 0.097$), and effort expectancy (Cohen's $f^2 = 0.079$) showed small to medium effects.

6. Discussion

6.1. Findings

This study, based on UTAUT models, examined potential predictors for GenAI adoption in new product development (NPD), including individual differences and perception factors. Key findings revealed performance expectancy and anthropomorphism as the strongest positive contributors to users' attitudes. This aligns with prior UTAUT research highlighting performance expectancy's significance (Cao et al., 2021; Sharma et al., 2024). In the context of NPD, factor analysis indicated a strong interconnection between performance expectancy and perceived anthropomorphism. Although anthropomorphism is widely researched in human-AI interaction studies (Araujo, 2018; Hui et al., 2023; Xie et al., 2023; Zhang & Patrick Rau, 2023), it is not commonly included in the UTAUT framework.

The strong association between performance expectancy and anthropomorphism can be attributed to users' belief that more human-like GenAI is highly intelligent and capable of delivering accurate, professional, or creative output effectively. This echoes recent research, suggesting that recent effective AI is increasingly viewed as team members instead of mere tools (Larson & DeChurch, 2020; Seeber et al., 2020; Zhang et al., 2021) and that anthropomorphic design significantly boosts positive user acceptance of AI (Rietz et al., 2019).

Our study also found that task-tool fitness was the strongest predictor with the largest effect size of intention to use GenAI in NPD. This factor also significantly enhances positive attitudes toward GenAI use. It refers to a perception that the GenAI tool is compatible with their NPD tasks, encompassing ease of use, efficiency, quality of assistance, and peer opinions on GenAI's suitability. While akin to the concept of task-technology fit in prior research (Goodhue & Thompson, 1995), one item initially categorized under social influence was surprisingly integrated into this factor. This integration may stem from NPD's collaborative nature, where team members' perceptions of GenAI's compatibility were likely influenced by peer views more than in other contexts. Our finding of the strong effects of task-tool fitness also aligns with a recent study about GenAI adoption in software engineering (Russo, 2024), which suggested that the adoption of GenAI was predominantly driven by the compatibility of GenAI tools within existing development workflows.

In addition to the primary predictors, this study also revealed that price value and effort expectancy were positively associated with attitudes and behavioral intentions. Price value's association with behavioral intentions aligns with prior UTAUT research on AI (Cabrera-Sánchez et al., 2021; Strzelecki, 2023), while its association with attitudes is less explored. Regarding effort expectancy, earlier studies showed it was positively associated with attitudes toward AI (Gansser & Reich, 2021; Strzelecki, 2023), but its association with behavioral intentions was inconsistent in different studies using AI for general purposes. These studies indicated either no significant associations (Cabrera-Sánchez et al., 2021; García De Blanes Sebastián et al., 2022) or positive associations (Gansser & Reich, 2021; Xiong et al., 2023). However, in work-specific or specialized contexts, it was consistently positively associated with behavioral intentions (Foroughi et al., 2023; Maican et al., 2023; Osta et al., 2022). Thus, our findings echo these consistent trends in specific contexts.

Most previous studies of AI adoption based on UTAUT suggested the insignificant effects of facilitating conditions (Cabrera-Sánchez et al., 2021; Yin et al., 2023), but our study revealed a positive association between facilitating conditions and users' behavioral intentions. The difference can be attributed to the heightened knowledge, collaboration, and ability to adapt to dynamic task changes in NPD (Hussein et al., 2014), leading to the requirement for using various GenAI tools for different tasks. This demonstrates the increasing need for outside assistance, including instructional materials and information access. Therefore, facilitating conditions have stronger effects on behaviors in this study than in previous research.

In the UTAUT model perception factors, only perceived risk did not predict attitudes or intentions in our study. Despite previous findings linking it negatively to behavioral intentions, our definition and measurement of perceived risk differed. Prior research often adopted the perceived risk theory, focusing on dimensions such as function, psychological, and societal risks (Bettman, 1973; Gansser & Reich, 2021; Stone & Grønhaug, 1993; Wu et al., 2022). However, this definition is infeasible here as suggested by the interviews in Study 1, and thus we finally included descriptions of perceived risks in individual or collective rights and dependence on technology. Later regression results indicated that even with concerns over privacy, job security, copyright issues, or societal impact, users still held positive attitudes toward GenAI and intended to use it for NPD. A possible reason was the privacy paradox, which refers to the inconsistency between privacy concerns and the actual behavior of users (Joinson et al., 2010). Users compare the risks and benefits to decide whether to adopt GenAI (Barth & de Jong, 2017; Kehr et al., 2014). In this study, the participants may have perceived that the benefits of using GenAI overrode the privacy concerns, as supported by the high rating scores on task-tool fitness.

Moreover, we found a significant positive association between AI self-efficacy and positive attitudes to GenAI tools. This finding aligns with previous research indicating that AI self-efficacy increases the intention to use AI technologies in daily activities (Hong, 2022), higher AI and ICT experience enhances the willingness to accept AI technology (Yi & Choi, 2023), and those confident in AI knowledge perceive greater benefits (Said et al., 2023). This finding is also consistent with earlier research suggesting that computer self-efficacy promotes the adoption of IT technologies (Ariff et al., 2012; Yeşilyurt et al., 2016). This study suggests similar results in NPD contexts. In addition, due to the growing perception that GenAI can be a team member instead of just a tool, distinctive characteristics of AI may be considered and integrated into the measurements of AI self-efficacy.

6.2. Implications

Previous UTAUT research has explored factors influencing GenAI acceptance but rarely in the NPD context. Studies for GenAI use for general purposes are hard to fully capture NPD's unique features of teamwork and diverse complex tasks. Our study found two new influential factors: a joint factor combining performance expectancy and anthropomorphism, and task-tool fitness. In addition, unlike prior work investigating the effects of personal innovativeness, we differentiated AI self-efficacy from openness to new experiences, showing that AI self-efficacy increased positive attitudes whereas openness had no significant effects. These insights offer useful contributions for refining UTAUT models specific to GenAI adoption in NPD settings.

The findings of this study suggest design implications for GenAI tools aimed at NPD teams. First, GenAI tool developers may consider anthropomorphic design and enhancing performance to improve users' attitudes towards using GenAI in NPD. This can be achieved by (1) enhancing the GenAI's ability to proactively participate in the NPD process, (2) increasing the similarity of GenAI's appearance and behaviors to humans, and (3) offering multiple AI communication styles to adapt to different users and contexts for accommodating diverse needs (Li & Suh, 2022; Li & Sung, 2021). The first approach suggests enabling proactive GenAI participation by making it aware of the states of tasks, contexts, and team members. This approach can provide more timely support and natural collaboration. In addition, frequent message interactions can bridge the gaps for chatbots without visual anthropomorphism (Go & Sundar, 2019) and align GenAI with human values and preferences (Xi et al., 2023). The second approach suggests designing more human-like visual representation cues and communication cues for GenAI, such as incorporating AI's emotional responses and providing visual cues to foster intimacy between users and GenAI and enhance overall satisfaction (Xie et al., 2023). Introducing human-like traits like politeness and a sense of humor is also beneficial (Diederich et al., 2019; Moussawi & Benbunan-Fich, 2021). The third approach suggests giving AI various communication styles to better suit the demands of different users, such as offering a more interpretative language style for those with high neuroticism, who may struggle to trust AI (Riedl, 2022).

Second, the GenAI tools need to be tailored for specific domains and NPD tasks to increase task-tool fitness. It requires the GenAI tool developers to identify and understand their target users' tasks accurately. For example, NPD teams may tend to use GenAI tools that understand domain-specific terminology or provide graphical styles suitable for the contexts, such as QuillBot for writing assistance and grammar checks, Jasper for marketing on social media, and Midjourney for visual design. Furthermore, although these current GenAI tools perform well in individual tasks, they lack the holistic ability to traverse within the workflow of developing products in a specific domain. It suggests a need for end-to-end GenAI solutions that integrate related functions across all stages of NPD in a specific domain, dynamically fit different tasks in ideation, conceptualization, design, prototyping, testing, and launch, and thereby streamline the entire NPD lifecycle.

Third, acceptance of GenAI in NPD can be increased by building online communities or platforms for GenAI users. Users can generate and share useful resources and tutorials and chat with or help each other via online forums. Similarly, previous research in online learning or branding contexts has also found that well-operated communities enable users to better learn the discussed topics and foster more positive attitudes towards the relevant topics (Cao & Yu, 2023; Kuo & Feng, 2013). Such a community-driven environment not only increases facilitating conditions and effort expectancy but also fosters a sense of social influence as well as AI self-efficacy, further encouraging users' adoption and effective use of GenAI tools in the NPD process.

6.3. Limitation

This study has some limitations in methodology and the factors considered. Methodological limitations encompass sampling and data analysis. First, both Study 1 and Study 2 predominantly recruited participants with relatively positive attitudes toward the use of GenAI in NPD. Future research may benefit from involving non-GenAI users to understand less favorable opinions, potentially revealing new factors and insights for GenAI tool design improvement. Second, exploratory factor analysis coupled with hierarchical regressions could not identify causal effects. Future research may adopt other methodologies, such as experiments or longitudinal studies.

In addition, this study excluded some potential factors associated with acceptance. First, from the UTAUT perspective, our focus on perception factors neglected the influence of specific functions or design features. Future research could integrate alternative theories and methodologies to explore how various AI functions and design features impact user acceptance. Second, it was also hard for the survey-based approach to study some objective factors such as individual training experiences and the actual behaviors of GenAI usage. Notably, participants' AI training backgrounds could significantly influence their acceptance (Yi & Choi, 2023), as evidenced by the significant associations between AI self-efficacy and attitudes in our study. Future research about more objective factors is required. Finally, to simplify our research, we did not incorporate factors affecting acceptance in previous studies, including trust (e.g., Roh et al., 2023), AI anxiety (e.g., Yin et al., 2023), technology fear (e.g., Cabrera-Sánchez et al., 2021), and specific risk dimensions such as ethical and functional concerns (e.g., Wu et al., 2022; Zhu et al., 2024). Future research may clarify the complex interrelationships among these factors and acceptance. For example, the effect of trust can be studied by more nuanced distinctions of cognitive or affective trust, or by examining the trust to general GenAI tools versus specific ones.

7. Conclusion

The study employed UTAUT models and conducted interviews with nine users and surveys with 309 valid responses to identify significant factors of the adoption of generative AI (GenAI) in new product development (NPD). It suggested a composite factor of performance expectancy and anthropomorphism as a primary positive contributor to attitudes, as well as indicating a strong association between them. Task-tool fitness emerged as the strongest predictor of intention to use GenAI in NPD, highlighting its compatibility with users' specific tasks. In addition, we also found positive influences of price value, effort expectancy, and facilitating conditions on attitudes or behavioral intentions. Notably, the perceived risk did not predict attitudes or intentions, possibly due to users prioritizing benefits over potential risks such as privacy concerns. Regarding individual differences, we distinguished the effects of AI self-efficacy and openness to new experiences, finding that higher AI self-efficacy was associated with positive attitudes whereas openness showed no significant association with attitudes. Overall, the findings suggest the increasing perception of GenAI as a team member in NPD and emphasize incorporating unique AI characteristics into UTAUT or other acceptance models. They also offer design implications for future GenAI tools for NPD.

Ethics statement

The Central Government of the People's Republic of China has issued a Circular on the Measures for Ethical Review, which covers the scope of ethical review that is not involved in our manuscript.

(https://www.gov.cn/zhengce/zhengceku/2023-02/28/content_5743658.htm)

Align with this circular, the authors' institution (East China University of Science and Technology) only offers ethical reviews for physiological experiments (e.g., eye tracking and EEG experiments), and does not offer ethical reviews for questionnaires and interviews in this article. Therefore, our study was not ethically involved based on university requirements and did not require ethical approval.

The subject informed consent form (translated from Chinese into English) used in the survey study is attached below.

Informed Consent Form

We appreciate your participation in this questionnaire survey. Before you decide whether to participate in this study, please read the following carefully.

This survey will be used for academic research to identify factors driving the use and attitudes toward generative AI tools in new product development tasks. Your answers will provide essential data for this study and contribute to the future design of generative AI tools.

The survey will be anonymous and have no impact or risk on your daily life. Your personal information for participating in this study will be kept strictly confidential. Any information that could reveal your identity will not be disclosed to members outside the study group.

In addition, upon completion of the study, you can enter a draw for a chance to win cash prizes in return if you are interested.

This survey is voluntary. If you have decided to agree to participate in this study and pledge to follow the study procedures as closely as possible, please continue. You can exit the survey at any time.

(Note: Since we collect data on the WJX Survey Platform, we were incapable to collect the participants' signature.)

Disclosure statement

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Appendix:

Questions for the structured part of the interview in study 1

Segment 1 general experience

1. What tasks and activities do you perform in new product development?
2. How did you come to know about GenAI tools?
3. When and under what circumstances did you first start using GenAI tools?
4. What GenAI tools have you used so far?
5. What GenAI tool do you use most frequently recently?

Segment 2 use of GenAI tools in different NPD phases and tasks

6. How often do you use GenAI tools to assist with NPD tasks?
7. At which stage of new product development do you typically use GenAI for assistance?
8. What tasks do you typically use GenAI tools to assist with?
9. What is the GenAI tool that you have most recently used frequently to assist with every task?
10. How do you use GenAI tools to assist with these tasks?

Segment 3 user comments on the effectiveness of GenAI tools

11. What kind of assistance do GenAI tools provide in NPD tasks?
12. What is your opinion about the assistance of GenAI tools?
13. Which capabilities of GenAI tools do you find most helpful for NPD tasks?
14. What tasks do you think GenAI performs well in the context of NPD?
15. What tasks do you think GenAI is lacking in the context of NPD?
16. For the GenAI tool that you most commonly use to assist with tasks, what do you see as its unique advantage?
17. Do you find the tools you are using easy to learn and use?
18. What difficulties have you encountered while using GenAI tools?
19. Are these difficulties able to be solved?
20. What are the ways of interaction with the AI tools that you have used?
21. What are the advantages and disadvantages of various ways of interaction of GenAI tools?
22. What is the attitude of people around you (mainly families, friends, and colleagues) towards using GenAI in NPD tasks?
23. What is the usage situation of GenAI among people around you?
24. Would you share your opinions of GenAI tools with people around you?
25. Is it easy for you to access and use this tool on different daily devices?
26. What kind of challenges have you encountered when accessing GenAI tools?
27. What kind of concerns do you have when using GenAI tools in NPD tasks?

Segment 4 outlook and expectations

28. What additional functionalities do you hope to see in future GenAI tools?
29. What optimizations would you like to see in future GenAI tools?
30. What do you think are the future development trends for GenAI tools?